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Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops

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ABSTRACT

Cultivation priority planning is a very important and vital step in suitable and sustainable revenue of agricultural land. The growth of urban areas and industrial intensification has contributed to a reduction in valuable agricultural lands and to various environmental impacts including climate change. This reduction in agricultural land severely impacts food production and food security. In order to effectively address this issue, spatial analytical and optimization methods based on evaluating multiple criteria decision are needed to evaluate the capability and suitability of available lands for current and future food production. The objective of this study is to implement the GIS and multi-criteria decision analysis (MCDA) techniques as an improved method of multi-criteria decision making for evaluating areas suitable for cultivation priority planning of maize, rape and soybean crops. For this purpose, 12,000 ha land which is located in Ardabil province, west-north of Iran was investigated by excavation of 167 soil profiles and 313 augers. After soil sampling and analysis, soils were classified in Aridisols. 24 soil series and 66 land units were identified and separated in study area. The several criteria had limitation for maize, rape and soybean cultivation in studying lands which the most limiting evaluation criteria including soil depth, slope, climate, pH, electrical conductivity, exchangeable sodium percentage, calcium carbonate and gypsum were selected for usage in prioritization models by principal component analysis and multi-dimensional scaling methods. Selected criteria were very important in growth of maize, rape and soybean. Simple additive weighting (SAW), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Fuzzy TOPSIS methods were used for cultivation priority planning of maize, rape and soybean crops in land units. Analytical Hierarchy Process (AHP) and Fuzzy AHP approaches were used to determine weight values of the criteria. Multivariate variance analysis proves significant difference among three methods at 0.05 probability level. With attention to allocated scores by prioritization models, crops cultivation priority was determined as maize, rape and soybean in land units, respectively and maize crop was preferred to other plants. The statistical analysis results with regard to mean comparison derived from least significant difference (LSD) test showed that Fuzzy TOPSIS method set cultivation priority planning of maize, rape and soybean crops for land units more accurately than the others, due to fuzzy TOPSIS method used appropriate values of criteria weights, twin comparing nature of alternative (crop) from positive and negative ideal, data standardization, mathematical equations and matrixes as well as fuzzy logic relations and principles for calculation of process performing. This study emphasizes the successful application of MCDA in dealing with complicated issues in the context of cultivation priority planning management. It is anticipated that, the integration of this developed framework in the planning policies of cultivation priority in developing countries as an effective tool for integrated regional land use planning can help in conducting better control over soil, land and environment losses.

1. Introduction

Land consolidation is considered as the most effective land management planning approach for solving land fragmentation, a problem that prevents rational agricultural development and rural sustainable development more generally (Demetriou, 2016). The

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decline of worthy agricultural land, as a result of constant urban and industrial growth, directly affects the ability to produce food at a large scale. So, agricultural production must be moved to other available land or land currently used for other purposes in order to meet global food demand (Lambin and Meyfroidt, 2011). This problem is more aggravated by the effects of global climate change and regional sensitivity increases (Montgomery et al., 2016). Moreover, increases in the frequency of risks such as drought, flooding, soil degradation, and regional shifts in crop production expense can seriously change economic markets, trade, and socioeconomic development (Schmidhuber and Tubiello, 2007). Consequently, urbanization and climate can severely impact on global food security (Montgomery et al., 2016).

Analysis of agricultural planning includes the consideration of a number of factors, including natural system constraints, compatibility with existing land uses, existing land use policies, and the availability of community facilities. The suitability techniques analyze the interaction between location, development actions, and environmental elements to classify the units of observation according to their suitability for a particular use (Malczewski, 2004). In reality, not all the conflicting objectives due to economic development, community or conservation interests are always taken into consideration, which could cause to political and manipulative, decisions. Modern planning theories such as communicative planning and actor-network theory focus on the fact that effective planning decisions should essentially consider all participants with a variety of discourse types and values (Mosadeghi et al., 2015). This encourages approaches for integrating very heterogeneous data, making them available to the various stakeholders to allow them to make more informed and less subjective decisions (Greene et al., 2010).

In the 1960s, the first multi-criteria decision making (MCDM) techniques were developed to facilitate difficulties in conforming different ideas and managing large amounts of complicated information in the decision-making process (Zopounidis and Pardalos, 2010). These capabilities have encouraged planners to combine MCDM with other planning tools such as geographical information system (GIS). Multi-criteria decision making involves a multi-stage process of i) defining objectives, ii) choosing the criteria to measure the objectives, iii) specifying alternatives, (iv) assigning weights to the criteria, and (v) applying the appropriate mathematical algorithm for ranking alternatives. MCDM allows accommodating the need for unbiased integration of modern planning objectives for independent identification and ranking of the most suitable planning solutions (Mosadeghi et al., 2009).

These spatial MCDM techniques are able to improve the transparency and analytic difficulty of the land use decisions (Hajkowicz and Collins, 2006). Practical applications of such spatial MCDM techniques have become more widespread in land suitability studies (Chang et al., 2008; Chen et al., 2010; Greene et al., 2010; Arciniegas et al., 2011; Kordi and Brandt, 2012; Elaalem, 2012; Akinci et al., 2013). Recent studies which show application of MCDM techniques in identifying the extent of future land-use zones are rare at local scale (Mosadeghi et al., 2013). The majority of previous MCDM applications mainly focus on using MCDM to rank the priority of predefined management options or planning scenarios (Xevi and Khan, 2005; Hajkowicz and McDonald, 2006; Ananda and Herath, 2008; Hajkowicz, 2008). Spatial MCDM, however, can be used not only to rank the priority of options and performing scenario analysis, but also to provide insight into the spatial extent of the alternatives (Arciniegas et al., 2011). This capability can help local land use planners to identify land use zones for future agriculture and urban development. It can be particularly useful in situations where planning instruments do not provide prescriptive guideline for local planning decisions.

Advanced MCDM methods including SAW, AHP, TOPSIS, Fuzzy set theory and Random set theory provide more sophisticated algorithms to process uncertain or inaccurate data (Zhang and Achari, 2010; Mosadeghi et al., 2015; Nguyen et al., 2015; Prakash and Barua, 2015; Wang, 2015; He et al., 2016; Kaliszewski and Podkopaev, 2016; Montgomery et al., 2016; Onat et al., 2016). The Fuzzy set theory techniques are considered the most common techniques for dealing with imprecise and uncertain problems (Zarghami et al., 2008; Zhang and Achari, 2010; Mosadeghi et al., 2013, 2015; Montgomery et al., 2016). Most of the empirical studies have applied Fuzzy techniques without a comparative analysis to study whether using more sophisticated techniques like Fuzzy AHP will correctly make a significant difference comparing conventional AHP. On the other hand, the few studies that have done comparative analysis in land suitability applications (Ertugrul and Karakasoglu, 2008; Elaalem, 2012; Kordi and Brandt, 2012; Elaalem, 2013) have mainly focused on arithmetic aspects such as differences in criteria weights, option rankings, or the effects of introducing uncertainty into their models. This need for comparative analyses carries an even greater imperative in the context of applying spatial MCDM methods to real-world cultivation priority planning decisions, where transparency and simplicity of the decision-making model is a key element during consultation with the stakeholders (Mosadeghi et al., 2015).

Multiple criteria decision analysis studies use a multitude of criteria and weights derived from expert knowledge in a spatial context and using geospatial datasets (Yu et al., 2011). Multiple criteria decision analysis outputs can be used for planning purposes and to facilitate decision-making processes and tools (Stauder, 2014; Malczewski and Rinner, 2015). Multi-criteria analysis has also been used for the development of spatial decision support systems to assist decision makers in addressing complex spatial problems and to analyze the trade-offs between alternatives for a given problem (Montgomery et al., 2016).

Maize, rape and soybean are important, strategic and principal as well as the major crops that are found in agricultural production systems. Cereals represent the major source of dietary protein for humans (Rótolo et al., 2015), and production figures for 2012 show that maize represented 34% of total global cereal production (FAO/STAT, 2014). Cereals such as maize are a key source of genetic material for food production, and integrate the net benefits of natural and human systems interaction through managed agro-ecosystems that we call agriculture (Rótolo et al., 2015). Soybean is grown world-wide as an important staple and commercial crop. The reserved area for planting soybean around the world is 99,501,101 ha (FAO/STAT, 2009). Soybean accounted for 56% of production of the main world oilseed crops in 2011 with a total production of 251.5 million tons (ASA, 2012). Rape seed contains both high oil and protein content. Rape is one of the main winter grain crops in Iran and world (Kamkar et al., 2014). The vast majority of maize, rape and soybean oil is used in the food industry, about one third in spreads and cooking oil and about two thirds in the commercial food service sector. These crops meal, the main by product of crushed seeds, is used as a high protein feed for intensive livestock, mainly in the pig, poultry and dairy industries.

Maize grows in the temperature range of 14–40 °C with optimum range 18–32 °C on many types of soils. It grows in the pH range 5.2–8.5 and optimum 5.8–7.8. Any yield reduction doesn't occur at an electrical conductivity (EC) $< 1\ dSm^{-1}$ (IIASA and FAO, 2012). Optimum values of available phosphorus and potassium for maize growth are $14\ mg\ kg^{-1}$ and $220\ mg\ kg^{-1}$, respectively (Gheibi et al., 2014). Soils are suitable for maize production that have exchangeable sodium percentage (ESP) < 6%, gypsum < 4% and calcium carbonate < 15% in useful soil depth (IIASA and FAO, 2012). The mean temperature range for a proper growth of oilseed rape is 8–30 °C, the optimum range being 12–22 °C. Rape can be produced on a wide variety of soils with optimum values of pH, EC, ESP, gypsum, calcium carbonate, available phosphorus and potassium, 5.6–7, $< 2\ dSm^{-1}$, < 8%, < 2%, < 12%, $> 18\ mg\ kg^{-1}$ and $> 195\ mg\ kg^{-1}$, respectively (IIASA and FAO, 2012; Noorgholipour et al., 2014). The temperature range for the growth of soybean is 15–40 °C. The growth is optimal at temperature between 20 and 30 °C. Soybean can be grown on soils with vast variety that have optimal values of pH 5.5–7.5, EC < 5.5 dSm^{-1}, ESP < 8%, gypsum < 0.2%, calcium carbonate < 15% (IIASA and FAO, 2012), available phosphorus $> 13\ mg\ kg^{-1}$ and potassium $> 160\ mg\ kg^{-1}$ in useful soil depth (Warncke et al., 2004).

Accordingly, the present research uses a case study to compare the outcomes of Simple Additive Weighting (SAW), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Fuzzy TOPSIS with regard to weights derived from Analytical Hierarchy Process (AHP) and Fuzzy AHP in cultivation priority planning for maize (*Zea mays*), oilseed rape (*Brasica napus* L.) and soybean (*Glycine* max.) crops in the northwest of Iran, Ardabil province, Dasht-e-Moghan region. Studies on use of the SAW, TOPSIS and fuzzy TOPSIS models for cultivation priority planning are very scarce. Application of these MCDA methods is a novelty in land evaluation planning due to their special algorithm. In this way, we also used GIS technique, a comprehensive data set on crops ecological requirements, climatic, topographic, soil data and statistical analysis.

2. Material and methods

2.1. Description of the study area

The study area (about 12,000 ha) is located in the Dasht-e-Moghan region (Ardabil province, northwest, Iran) (Fig. 1), between 39° 21′ to 39° 28′ N latitude and 47° 34′ to 47° 48′ E longitude. This area has three major physiographic units: upper terraces and plateaus, alluvial fans and piedmont plain. The soil temperature and moisture regimes are “Thermic” and “Aridic border on xeric”, respectively with regard to Newhall program (USDA, 2012). According to the US Soil Taxonomy System the dominant soils of the study area are Aridisols (Soil Survey Staff, 2014b). This area is characterized with a little rain in winter and a relatively hot arid in summer. The amount of annual rainfall is low and mostly falls in spring and autumn. The maximum rainfall is recorded in October, reaching about 34.3 mm and the mean annual precipitation is 268.5 mm in Pars-Abad station. Temperature is high during the summer months and relatively low in winter with annual mean 15.2 °C. The hottest temperature is recorded in July, reaching about 27.2 °C and the coldest month is January, reaching about 3.7 °C. Potential evaporation is low (20.2 mm/month) in December and January when the temperature is comparatively low. Potential evaporation value is high (185.5 mm/month) in July when the temperature is comparatively high. The altitude is 183 to 310 m. The area was formed in the latter part of the Miocene and the beginning of the Pliocene and Eocene periods, the surface of the area is essentially occupied by formations from the Quaternary (Ghorbani, 2013).

2.2. Processing of digital image and elevation contour layer

Processing of digital images for Landsat 8 Thematic Mapper (TM) satellite image (path 167, row 33) with a spatial resolution of 30 m acquired during 2015 was performed using Erdas Imagine software. The original scan line corrector image has been replaced with estimated values based on histogram-matched scenes to improve the utility of the scan line corrector data. The TM image was stretched using linear 5%, smoothly filtered, and their histograms were matched. The used image was geometrically corrected using a rectification method. Elevation contour lines and points were used to generate raster Digital Elevation Model (DEM) with resolution of 5 × 5 m using ArcGIS 10.3.1 software. The physiographic units were distinguished using the processed satellite image, DEM and Google earth image of study area and classified into groups. DEM map was smoothly filtered then converted to slope map.

2.3. Fieldwork, laboratory analyses and preparation of soil and land units' maps

Field studies were carried out to identify the physiographic units and the reality of soils interpretation. For this purpose, soil sampling points e.g. soil profiles were dug with between distances 1000 m. Soil changes between two profiles were controlled by an auger, if soil changes were considerably auger convert to profile. Finally, a total of 480 observation points including 167 soil profiles and 313 augers were excavated to check the accuracy of mapping units. A detailed morphological description of the studied soil profiles was elaborated on the basis outlined by Soil Survey Staff (2012). Soil samples have been collected from all of the horizons soil profiles and analyzed for physical and chemical characteristics using the standard analytical methods as described in Soil Survey Staff (2014a).

Soil samples were air dried, well crushed, sieved and particles < 2 mm were used for chemical analyses. Soil color in both wet and dry samples, particle size distribution, soil bulk density, exchangeable sodium percentage (ESP), electrical conductivity (EC), soil reaction (pH), organic carbon content (OC), calcium carbonate, gypsum, available potassium, available phosphorus and cation exchange capacity (CEC) were determined by Munssel color charts, hydrometric method, clod method, ammonium acetate using flame photometer, saturation soil paste, soil water suspension 1:2, the modified Walkley and Black method, volumetrically using calcimetery method, acetone method,

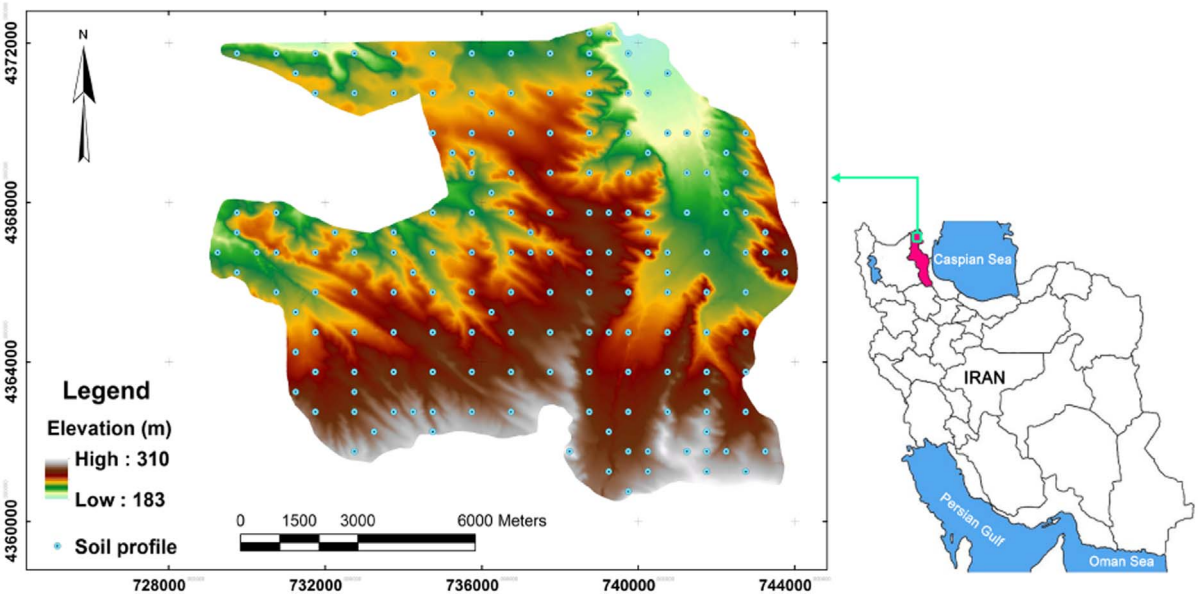

Fig. 1. Location of the study area and soil profiles.

extracted in the 1.0 N ammonium acetate solution (pH = 7) using flame photometer, extracted in 0.5 N $NaHCO_3$ solution (pH 8.5) using spectrophotometer and sodium oxalate at a pH of 8.2, respectively.

Finally, delineation of soil taxonomic units was determined using soil data information derived from soil profiles sampling analyzes and information of processed satellite and Google earth images. Prepared slope polygon map was overlaid with a soil taxonomic units' map which produced land units (mapping units) map, in this way the soil taxonomic unit delineation was incidentally protected.

2.4. Selection of the diagnostic criteria

For assessing of land units, effective criteria for crops (maize, oilseed rape and soybean) growth should be selected. The number of these criteria should be eight according to land suitability evaluation principles (Sys et al., 1991). For this purpose, Multi-dimensional Scaling (MDS) and Principal Component Analysis (PCA) were used for criteria selection. MDS method advises for separation similar criteria by Euclidean distance (Wang, 2012). In this study, MDS method was performed on limiting criteria for crops growth and eight criteria were selected with regard to Euclidean distance. Also, PCA method was used for selection of important criteria on crop yield (Da Sheng et al., 2011). In PCA analysis principal components that have Eigen value > 1, coefficient's maximum values of criteria for these principal components were distinguished as effective criteria.

2.5. Determination of criteria weights

2.5.1. AHP

The weights of criterion were calculated in four steps in pair-wise comparison matrix i.e. (1) formation of judgments, (2) calculation of assigned ranks, (3) preparation of normalized pair-wise comparison matrix and finally, (4) calculation of weights. Judgments of ranks were formed based on expert opinion and compared in pair-wise comparison matrix. The pair-wise comparison analysis helps for decision makers to assign different levels of importance of criteria involved in crops prioritization. Priority determination analysis studies have assigned criteria weights according to their relative importance and land characteristics (Elaalem, 2012). The cell values of pair-wise comparison matrix were divided by sum of the column to obtain the cell values in normalized pair-wise comparison matrix and averaged in row to calculate the weights of criterion (Akinci et al., 2013). These, calculated weights were scaled from 0 to 1 in ascending order to maintain hierarchy according to their importance in land suitability for wheat cultivation. The accuracy of the calculated weights pair-wise comparison matrix depends on the consistency of judgments of ranking the criterion. Consistency ratio measures logical inconsistency of the judgments and facilitate identification of possible errors (Cengiz and Akbulak, 2009). Saaty (2008) suggests acceptable consistency ratio values up to 0.1. Therefore, it is suggested that pair-wise comparison matrix should be revised according to improved judgment, if the consistency ratio excides the upper limit 0.1.

2.5.2. Fuzzy AHP

The membership function for a triangular fuzzy number (TFN) Ã shown in Fig. 2 on space $\mu \rightarrow [0, 1]$ with basis denoted as (l, m, u) can be defined as follows in Eq. (1):

$$\mu\widetilde{A}_{(x)} = \begin{cases} 0, & x \le l \\ \frac{x-l}{m-l}, & l \le x \le m \\ \frac{x-u}{m-u}, & m \le x \le u \\ 0, & otherwise \end{cases} \quad (1)$$

The parameters (l, m, u) are real numbers which indicate the lowest possible value, the most favorable value, and the highest possible value ($l < m < u$), respectively that describe a fuzzy case. The operational

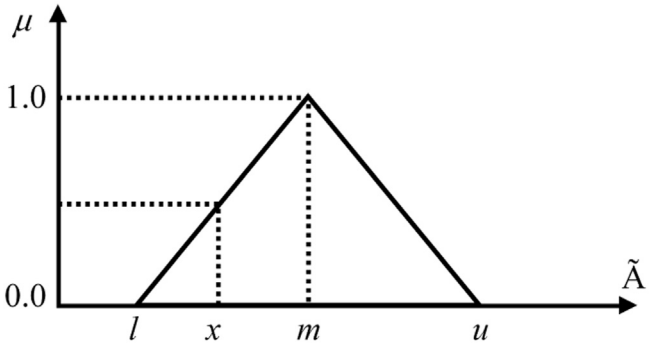

Fig. 2. Illustration of fuzzy triangular number (TFN).

rules (algebraic operations) for two TFNs $\tilde{A} = (a_1, a_2, a_3)$ and $B = (b_1, b_2, b_3)$ are:

$$\tilde{A} + B = (a_1, a_2, a_3) + (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3)$$

$$\tilde{A} \times B = (a_1, a_2, a_3) \times (b_1, b_2, b_3) = (a_1 b_1, a_2 b_2, a_3 b_3)$$

$$\tilde{A}^{-1} = (1/a_3, 1/a_2, 1/a_1)$$

where + denotes extended summation of two TFNs, and × denotes the extended multiplication.

The traditional AHP (Saaty, 1980) is extensively used in MCDA. In comparison with other methods, it is more easily understood in context of mathematical calculations. Despite its wide and successful applications, it has always been criticized for its inability in managing uncertainty resulting from relating whole numbers to decision makers understanding. It is thus ineffective in application to ambiguous decision problems which are prevalent in real world (Javanbarg et al., 2012). Therefore, the integration of fuzzy set theory with traditional AHP, which employs the principles of decomposition; pair-wise comparisons; priority vector aggregation and synthesis (Taylan et al., 2014; Prakash and Barua, 2015) is vital in dealing with sources of uncertainty. It has a potential to map the perceptions, incomplete information and approximations to produce decisions by employing the membership functions. The use of fuzzy extension of AHP, Fuzzy AHP, is proper in solving the hierarchical rating of fuzzy decision problems. It allows the decision maker to concentrate on specific sub-criteria to make pair-wise comparison among the criteria that have the same root depending on their position on the hierarchy structure which yields the relative tradeoff in the form of comparison matrices (Del Vasto-Terrientes et al., 2015). The extent analysis of Fuzzy AHP can be used to derive the priority weights from fuzzy comparison matrices. The following steps explain the procedure:

Step 1. Translating the linguistic terms used by decision makers to express the comparative judgments among the main criteria with respect to the overall goal, and evaluation criteria with respect to their main criterion into TFNs. The arrangement of the comparison matrices will be as below (Nadaban et al., 2016; Zyoud et al., 2016):

$$\widetilde{A} = (\tilde{a}_{ij})_{n\times n} = \begin{bmatrix} (1,1,1) & (l_{12}, m_{12}, u_{12}) & \cdots & (l_{1n}, m_{1n}, u_{1n}) \\ (l_{21}, m_{21}, u_{21}) & (1,1,1) & \cdots & (l_{2n}, m_{2n}, u_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (l_{n1}, m_{n1}, u_{n1}) & (l_{n2}, m_{n2}, u_{n2}) & \cdots & (1,1,1) \end{bmatrix} \quad (2)$$

The range of used values in Fuzzy AHP utilizes the scale that is shown in Table 1 (Tesfamariam and Sadiq, 2006).

Step 2. For the aggregation of the preferences of t (decision makers) in order to build final pair-wise comparison matrix, the following method is used (Zyoud et al., 2016):

Table 1
Fuzzy numbers used for making pair-wise comparisons.

Relative importance	[a]Fuzzy scale	[b]Definition	Explanation
$\bar{1}$	(1, 1, 1)	Equal importance	Intermediate values between two adjacent judgments
$\bar{3}$	(3 − Δ[c], 3, 3 + Δ)	Weak importance	Experience and judgment slightly favor one activity over another
$\bar{5}$	(5 − Δ, 5, 5 + Δ)	Essential or strong importance	Experience and judgment strongly favor one activity over another
$\bar{7}$	(7 − Δ, 7, 7 + Δ)	Demonstrated importance	One activity is strongly favored and demonstrated in practice
$\bar{9}$	(8, 9, 9)	Demonstrated importance	One activity is strongly favored and demonstrated in practice
$\bar{2}$, $\bar{4}$, $\bar{6}$, $\bar{8}$	(x − Δ, x, x + Δ)	Intermediate values between two adjacent judgments	When compromise is needed
$\frac{1}{\bar{x}}$	(1/(x + Δ), x, 1/(x − Δ))		
$\frac{1}{\bar{9}}$	(1/9, 1/9, 1/8)		

[a] The intensity of importance definition is in accordance with the description proposed by Saaty (1980).
[b] Minimum, most likely, and maximum values.
[c] Δ is a fuzzification factor.

$$\begin{cases} \widetilde{W}_{ij} = (Lw_{ij}, Mw_{ij}, Uw_{ij}) \\ Lw_{ij} = min_t(Lw_{ijt}),\ Mw_{ij} = \frac{1}{T}\sum_{t=1}^{T} Mw_{ijt},\ Uw_{ij} = max_t(Uw_{ijt}) \end{cases} \quad (3)$$

$\widetilde{W}_{ij}$ = the triangular fuzzy weight of the i^{th} criterion in comparison with the j^{th} criterion.

Step 3. Determining the weights for the involved criteria. The synthetic pair-wise comparison matrix is computed using geometric mean method. Geometric mean r_i is defined as:

$$\begin{cases} r_i = \left((Lw_{ij1} \times Lw_{ij2} \times_{...} \times Lw_{ijn})^{\frac{1}{n}}, (Mw_{ij1} \times Mw_{ij2} \times_{...} \times Mw_{ijn})^{\frac{1}{n}}\right. \\ \quad \left., (Uw_{ij1} \times Uw_{ij2} \times_{...} \times Uw_{ijn})^{\frac{1}{n}}\right) \\ r_i = (Lw_{gm}, Mw_{gm}, Uw_{gm}) \end{cases} \quad (4)$$

gm: geometric mean.

Step 4. The weight for each criterion is determined. This is done by normalizing the matrix.

$$\begin{cases} w_{c1} = r_{c1} \times (r_{c1} + r_{c2} +_{...} + r_{cn})^{-1} \\ w_{c1} = \begin{pmatrix} (Lw_{gmc1} \times (Uw_{gmc1} +_{...} + Uw_{gmcn})^{-1}), (Mw_{gmc1} \\ \quad \times (Mw_{gmc1} +_{...} + Mw_{gmcn})^{-1}), \\ (Uw_{gmc1} \times (Lw_{gmc1} +_{...} + Lw_{gmcn})^{-1}) \end{pmatrix} \end{cases} \quad (5)$$

w_{c1}: fuzzy weight (triangular fuzzy number) of first criterion, *c1* = first criterion in comparison matrix.

2.6. Determination methods of cultivation priority

2.6.1. Simple additive weighting (SAW)

SAW is one of the most often used techniques for resolving spatial decision analysis problems. The decision maker directly assigns weights of relative importance to each attribute. A total score is then obtained for each alternative (crop) by multiplying the importance weight assigned for each attribute by the scaled value given to the alternative for that attribute and summing the products over all attributes. The normalized value for positive criteria is calculated as fallow:

$$n_{ij} = \frac{g_{ij}}{g_{max}} \quad i = 1, ..., m \qquad j = 1, ..., n \quad (6)$$

And for negative criteria:

$$n_{ij} = \frac{g_{min}}{g_{ij}} \quad i = 1, ..., m \qquad j = 1, ..., n \quad (7)$$

$$\text{Final score} = \sum (w_{g_{ij}} \times n_{ij}) \qquad \sum w_{gij} = 1 \quad (8)$$

where g_{ij}: criterion value, g_{max}: maximum value for each positive criterion, g_{min}: minimum value for each negative criterion, n_{ij}: normalized value.

2.6.2. TOPSIS

The TOPSIS (technique for order performance by similarity to ideal solution) was first developed by Hwang and Yoon (1981). According to this technique, the best alternative would be the one that is nearest to the positive ideal solution and farthest from the negative ideal solution (Ertugrul and Karakasoglu, 2007). The positive ideal solution is a solution that maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Wang and Elhag, 2006). In short, the positive ideal solution is composed of all best values attainable from the criteria, whereas the negative ideal solution consists of all worst values attainable from the criteria (Wang, 2008). There have been lots of studies in the literature using TOPSIS for the solution of MCDM problems (Dagdeviren et al., 2009). The computational steps of the TOPSIS method are presented in the following steps (Lozano et al., 2016; Onat et al., 2016):

Step 1. Establishing a performance decision matrix:

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad (9)$$

Step 2. Calculating the normalized decision matrix. The normalized value r_{ij} is calculated as follows and normalized decision matrix as Eq. 11:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}; \quad (i = 1, 2, ..., m); \quad (j = 1, 2, ..., n) \quad (10)$$

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (11)$$

Step 3. Calculating the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as follows:

$$V_{ij} = R_{ij} \times W_{n\times n} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \quad (12)$$

where w_j is the weight of the j^{th} criterion or attribute and $\sum_{j=1}^{n} W_j = 1$.

Step 4. Determining the positive ideal (A_i^+) and negative ideal (A_i^-)

solutions.

$$A_i^+ = \{(max\, v_{ij} \mid j \in J), (min\ v_{ij} \mid j \in J'), (i = 1, 2, ..., m)\} = \{v_1^+, v_2^+, ..., v_n^+\} or \{v_j^+\} \quad (13)$$

$$A_i^- = \{(min\, v_{ij} \mid j \in J), (max v_{ij} \mid j \in J'), (j = 1, 2, ..., n)\} = \{v_1^-, v_2^-, ..., v_n^-\} or \{v_j^-\} \quad (14)$$

where J and J' are the sets of criteria "with positive effect" and criteria "with negative effect", respectively.

Step 5. Calculating the separation measures using the m-dimensional Euclidean distance. The separation measures of each alternative from the positive ideal solution and the negative ideal solution, respectively, are as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^+)^2}, \quad i = 1, 2, ..., m \quad (15)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}, \quad j = 1, 2, ..., n \quad (16)$$

Step 6. Calculating the relative closeness to the ideal solution:

$$CC_i^+ = \left[\frac{D_i^-}{D_i^+ + D_i^-}\right]; \quad 0 \le CC_i^+ \le 1; \quad i = 1, 2, ..., m \quad (17)$$

Step 7. Ranking preference orders. Choose an alternative (crop in this study) with maximum value of CC_i or ranking alternatives according to CC_i value in descending orders.

2.6.3. Fuzzy TOPSIS

The TOPSIS method is a multiple criteria decision making technique proposed by Hwang and Yoon (1981) to identify a solution from a finite set of options. Its principle is based on the fact that, the chosen option should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution (Taylan et al., 2014; Beikkhakhian et al., 2015). The Fuzzy TOPSIS technique was proposed by Chen (2000) to solve multi-criteria decision making problems under fuzzy environment (Junior et al., 2014) and to deal efficiently with uncertainty in the evaluations and judgments. By this technique, the options have to be evaluated with respect to a set of criteria and as the linguistic experts' opinions are subjective, vague, and imprecise in nature (Islam et al., 2013), fuzzy set theory has to be used, and TFNs can be used to express the linguistic expert's opinions. The steps of Fuzzy TOPSIS can be given as in the following (Nadaban et al., 2016; Zyoud et al., 2016):

Step 1. The importance weight of criteria $\widetilde{w}_{ij}$ which describes the aggregated fuzzy weight of the j^{th} criterion with respect to the overall goal, Cj (j = 1, …,n), given by the N^{th} decision maker and is calculated by Fuzzy AHP technique will be fed to Fuzzy TOPSIS.

Step 2. Aggregating ratings of options: To build the decision matrix, the linguistic ratings of an option by different decision makers expressed in terms of TFNs have to be aggregated. In case, there are N decision makers, and the rating of the i^{th} option for j^{th} criterion is $\widetilde{X}_{ij} = (x_{ija}, x_{ijb}, x_{ijc})$, the aggregated rating can be expressed by the following equations:

$$\begin{cases} \widetilde{X}_{ija} = \frac{1}{N}(x_{ija}^1 + x_{ija}^2 + ... + x_{ija}^N) \\ \widetilde{X}_{ijb} = \frac{1}{N}(x_{ijb}^1 + x_{ijb}^2 + ... + x_{ijb}^N) \\ \widetilde{X}_{ijc} = \frac{1}{N}(x_{ijc}^1 + x_{ijc}^2 + ... + x_{ijc}^N) \end{cases} \quad (18)$$

Step 3. Building and normalizing the fuzzy decision matrix from the aggregated ratings of options as follows:

$$\widetilde{DM} = \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \cdots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \cdots & \widetilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \cdots & \widetilde{x}_{mn} \end{bmatrix} \quad (19)$$

where, $\widetilde{X}_{ij}$ is the aggregated fuzzy rating of i^{th} option with respect to j^{th} criterion and, i = 1, 2, 3, …, m, j = 1, 2, 3, …, n. The normalization of the decision matrix $\widetilde{DM}$ has to be carried out by the linear scale transformation as follows:

$$c_j^+ = Max\ x_{ijc}, \quad j \in B; \tilde{u}_{ij} = \left(\frac{x_{ija}}{c_j^+}, \frac{x_{ijb}}{c_j^+}, \frac{x_{ijc}}{c_j^+}\right) \quad (20)$$

$$a_j^- = Min\ x_{ija}, \quad j \in C; \tilde{u}_{ij} = \left(\frac{a_j^-}{x_{ijc}}, \frac{a_j^-}{x_{ijb}}, \frac{a_j^-}{x_{ija}}\right) \quad (21)$$

where, $c_j{}^+$ is used for criteria "with positive effect" and $a_j{}^-$ is used for criteria "with negative effect". $\tilde{u}_{ij}$ is the normalized rating of the option, and the normalization matrix is as follow:

$$\widetilde{U} = \begin{bmatrix} \tilde{u}_{11} & \tilde{u}_{12} & \cdots & \tilde{u}_{1n} \\ \tilde{u}_{21} & \tilde{u}_{22} & \cdots & \tilde{u}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{u}_{m1} & \tilde{u}_{m2} & \cdots & \tilde{u}_{mn} \end{bmatrix} \quad (22)$$

Step 4. The fuzzy weighted normalized decision matrix will be calculated by multiplying the weights of the evaluation criteria $\widetilde{w}_j$ by the elements of the normalized fuzzy decision matrix $\tilde{u}_{ij}$ according to the following equations:

$$\tilde{v}_{ij} = \tilde{u}_{ij} \times \widetilde{w}_j = \left(\frac{x_{ija}}{c_j^+}, \frac{x_{ijb}}{c_j^+}, \frac{x_{ijc}}{c_j^+}\right) \times (w_1, w_2, w_3) \quad (23)$$

$$\tilde{v}_{ij} = \tilde{u}_{ij} \times \widetilde{w}_j = \left(\frac{a_j^-}{x_{ijc}}, \frac{a_j^-}{x_{ijb}}, \frac{a_j^-}{x_{ija}}\right) \times (w_1, w_2, w_3) \quad (24)$$

$$\widetilde{V} = \widetilde{U} \times \widetilde{W} = \begin{bmatrix} \tilde{v}_{11} & \tilde{v}_{12} & \cdots & \tilde{v}_{1n} \\ \tilde{v}_{21} & \tilde{v}_{22} & \cdots & \tilde{v}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{v}_{m1} & \tilde{v}_{m2} & \cdots & \tilde{v}_{mn} \end{bmatrix} \quad (25)$$

where, i = 1, 2, 3, …, m, j = 1, 2, 3, …, n, and the element of $\tilde{v}_{ij}$ is a weighted normalize fuzzy number, and their elements are in the range of [0, 1].

Step 5. Defining the Fuzzy Positive Ideal Solution (FPIS, S^+), and the Fuzzy Negative Ideal Solution (FNIS, S^-): the positive ideal solution (PIS) allows maximizing the benefit attributes and minimizing the cost attributes. On the contrary, the negative ideal solution (NIS) does the opposite, by minimizing the benefit attributes and maximizing the cost attributes. The option which is closer to the PIS, and farther from the NIS is the leading solution (Islam et al., 2013; Junior et al., 2014). The (FPIS, S^+) and (FNIS, S^-) can be defined according to the following equations:

$$S^+ = (\tilde{v}_1^+, \tilde{v}_2^+, ..., \tilde{v}_n^+), \ \tilde{v}_j^+ = (Max\, \tilde{v}_{ija}, Max\, \tilde{v}_{ijb}, Max\, \tilde{v}_{ijc}) \quad (26)$$

$$S^- = (\tilde{v}_1^-, \tilde{v}_2^-, ..., \tilde{v}_n^-), \ \tilde{v}_j^- = (Min\, \tilde{v}_{ija}, Min\, \tilde{v}_{ijb}, Min\, \tilde{v}_{ijc}) \quad (27)$$

Step 6. Computing the separation distances of each option from the FPIS and the FNIS to provide a measure of the closeness of the options from the FPIS and the FNIS according to the following equations, which provide separation distance for two TFNs by the vertex method:

$$d(\tilde{v}_{ij}, \tilde{v}_j^+) = \sqrt{\frac{1}{3}[(\tilde{v}_{ija} - max\,\tilde{v}_{ija})^2 + (\tilde{v}_{ijb} - max\,\tilde{v}_{ijb})^2 + (\tilde{v}_{ijc} - max\,\tilde{v}_{ijc})^2]} \quad (28)$$

$$d(\tilde{v}_{ij}, \tilde{v}_j^-) = \sqrt{\frac{1}{3}[(\tilde{v}_{ija} - min\,\tilde{v}_{ija})^2 + (\tilde{v}_{ijb} - min\,\tilde{v}_{ijb})^2 + (\tilde{v}_{ijc} - min\,\tilde{v}_{ijc})^2]} \quad (29)$$

$$D_i^+ = \sum d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad i = 1, 2, 3, \ldots, m, \quad j = 1, 2, 3, \ldots, n \quad (30)$$

$$D_i^- = \sum d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1, 2, 3, \ldots, m, \quad j = 1, 2, 3, \ldots, n \quad (31)$$

Step 7. Computing the relative closeness coefficient (CC_i) of each option with respect to the (FPIS, S^+), and (FPIS, S^-) using the following equation:

$$CC_i = \left[\frac{D_i^-}{D_i^+ + D_i^-}\right], \qquad i = 1, 2, \ldots, m \quad (32)$$

Step 8. Defining the ranking of the options according to the values of closeness coefficients (CC_s), in descending order. The best option will be the closest to the FPIS and the farthest to the FNIS.

3. Results and discussion

3.1. Surveyed soils and separated land units

According to soil analysis and satellite and Google earth images, 24 soil series were surveyed in study area (Fig. 3). Family names of these soils are presented in Table 2. Integration soil taxonomic units with slope layer produced 66 mapping units (land units) that their delineation is illustrated in Fig. 3.

3.2. Selected useful criteria for crops growth

Criteria values of soil texture, coarse fragment, soil depth, gypsum, $CaCO_3$, available water capacity (AWC), pH, OC, available phosphorus and potassium, CEC, EC, ESP, slope, flooding, drainage and study area climate were determined by influence of weight coefficients in mapping units. Among these criteria, soil depth, gypsum, $CaCO_3$, AWC, pH, OC, available phosphorus and potassium, EC, ESP, slope and climate had limitation for maize, rape and soybean cultivation. With regard to land suitability assessment principles, eight criteria should be selected for assessing. MDS method was performed on limiting criteria for crops growth and AWC, OC, available potassium and phosphorus were separated from other criteria (Fig. 4), because mentioned criteria were closer to each other regarding Euclidean distance. PCA was carried out on criteria and results are presented in Table 3. In PCA analysis five principal components had Eigen value more than 1. Coefficient's maximum values of criteria for PC1 to PC5 were distinguished. OC, available potassium and phosphorus had minimum coefficient on principal components, therefore these criteria were separated. AWC had maximum coefficient but it had low limitation only in land units 24 and 25 (these units have little area) and had not limitation in the other land units. These land units also had OC limitation and both of AWC and OC limitations will be improved by fertilizer addition. The limitation of OC, available potassium and phosphorus can be amended by application of biologic and manure fertilizers in land units of study area. Therefore, eight criteria including soil depth, gypsum, $CaCO_3$, pH, EC, ESP, slope and climate were selected via statistical methods and criteria limitation analyzing in mapping units were used in priority determination approaches, finally. Also, our surveying investigations in study area distinguished that selected criteria are correct and have the most limitation for maize, rape and soybean cultivation with attention to study area conditions, soil and land requirements.

3.3. Calculated weights, fuzzy weights and check for consistency

Each criterion has special effect on crops growth. Decision maker should be able to assign different levels of criteria importance in prioritization planning correctly. Prioritization analysis studies have assigned criteria weights according to their relative importance and land characteristics (Elaalem, 2012). In the first phase, the data for pair-wise comparisons were analyzed using AHP algorithms to obtain the final weights for each criterion and results are presented in Table 4. Various techniques are used to compute the final fuzzy weights, such as, computation of the eigenvector, arithmetic mean, geometric mean, etc. Preliminary investigation was carried out using these techniques and showed no significant difference. Consequently, for the ease of implementation, the geometric mean is adopted to estimate the weights. The geometric mean is consistent and upholds separability, unanimity and homogeneity which have to be satisfied to aggregate individual judgments' (Ananda and Herath, 2008). Fuzzy arithmetic operations (described in Table 1) are utilized over matrix to compute the fuzzy weights according to mentioned steps in material and method section. Derived Fuzzy weights (TFNs) are presented in Table 5.

Consistency is important in human thinking, which enables us to order the world according to dominance. It is paramount to ensure that there is consistency in the pair-wise comparisons. The pair-wise comparisons of the fuzzy judgment matrix are prone to inconsistency and error in the preference responses of people, and as a result often become inconsistent. The AHP introduces a consistency measure to avoid this problem and estimate the relative weight in the presence of inconsistency in responses. The threshold of the consistency rate (CR) is 10% (Saaty, 2008). The pair-wise comparison indices (relative importance) of the judgment matrix are TFNs, however, the CR is evaluated for the most likely value for example in (0.25, 0.35, 0.45) 0.35 is most likely value (Tesfamariam and Sadiq, 2006). In this study, the pair-wise comparisons were consistent with the overall mean consistency ratio (CR) for all criteria of < 0.1. These values are mentioned for all criteria of AHP and fuzzy AHP methods in Tables 4 and 5, respectively.

3.4. Applying MCDA techniques for cultivation priority planning

Rating values were calculated for selected criteria on maize, rape and soybean crops according to Table 6. These values were used in prioritization methods that interpreted in material and method section clearly. Scores derived from SAW, TOPSIS and Fuzzy TOPSIS methods are presented in Table 7. Cultivation priority was set as maize-rape-soybean in all of the land units (Table 7) that this output was result of each three methods. Soybean is sensitive to soil gypsum in comparison to maize and rape (Table 6). In land units with high soil gypsum, for example units 6, 7, 8 and 17 soybean had the lowest score. Maize had the most score in land units that had high soil gypsum, because maize is more tolerance than soybean and rape to gypsum. Slope, ESP, soil depth and EC had moderate limitations in some of land units. Calcium carbonate amount was considerable in all of the land units but didn't cause severe limitation for growth of crops. Available potassium hadn't any limitation while phosphorus imposed limitation for crops which can be amended with application of biologic and manure fertilizers in land units of study area. In general, land units which had low score for maize, their criteria limitations were high and vice versa.

3.5. Discussion on prioritization methods

The initial comparison shows higher accuracy for Fuzzy AHP options. On the other words, compared to the conventional AHP, Fuzzy AHP outputs are more suitable to determine criteria weights. The differences between two models were more apparent for all crops on all of the criteria (Tables 4 and 5). The least CR output values were seen for the Fuzzy AHP method in the criteria weights determination. The stability of the Fuzzy AHP outputs particularly in the criteria weights

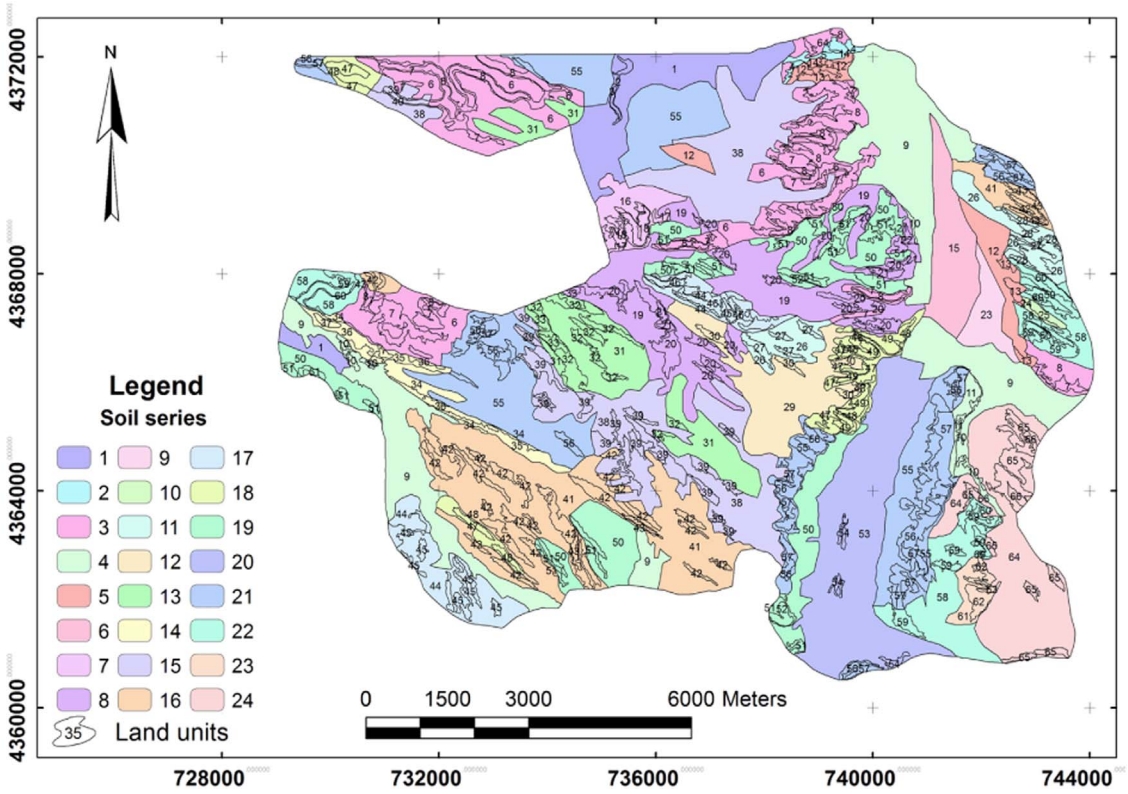

Fig. 3. Distribution of soil series (soil taxonomic units) and land units in study area.

Table 2
Family names of soil taxonomic units according to Soil Survey Staff (2014b).

Soil seri number	Family name
8, 13, 21, 24	Fine, mixed, superactive, thermic Xeric Calcigypsids
1, 16, 17	Fine, mixed, active, thermic Xeric Calcigypsids
9	Fine, mixed, superactive, thermic Xeric Haplogypsids
5	Fine, mixed, active, thermic Xeric Haplocalcids
2	Fine, mixed, active, thermic Sodic Xeric Haplocalcids
7, 22	Fine, mixed, superactive, thermic Xeric Natrigypsids
12, 15, 19	Fine, gypsic, thermic Xeric Calcigypsids
6, 20	Fine, mixed, superactive, thermic Sodic Haplogypsids
4	Fine, mixed, superactive, thermic Xeric Haplocambids
10	Fine, gypsic, thermic Xeric Argigypsids
3	Very fine, gypsic, thermic Calcic Argigypsids
11	Fine-gypseous, hypergypsic, thermic Xeric Natrigypsids
14, 18	Fine, gypsic, thermic, Xeric Natrigypsids
23	Fine, mixed, active, thermic Xeric Natrargids

echoes that Fuzzy AHP not only introduces more valid and trusty outputs, but also enhances the stability of the outcomes where a decision making model involves more options or alternatives. The MCDA outputs were more sensitive to the criteria weight changes for the crops (Table 7), where SAW, TOPSIS and Fuzzy TOPSIS models identified different results. However, Fuzzy TOPSIS performed the prioritization process better than the others with the maximum of score mean for maize, in our study area.

Multivariate analysis and Levene's test of equality of error variances for the three models on maize, rape and soybean crops also showed that all models had significant difference ($p < 0.05$) (Tables 8 and 9) and the higher accuracy was appertained to the Fuzzy TOPSIS model according to mean comparison by LSD test (Table 10). It is important to emphasize this result that the outputs in the Fuzzy TOPSIS model were more suitable than SAW and TOPSIS models in all of the land units, because Fuzzy TOPSIS model used TFNs weights for criteria in cultivation priority determination. Models which are sensitive to the criteria weight changes showed that the degree of priority accuracy of crops was almost independent to changes in criteria weights. These results were consistent with the findings of Nadaban et al. (2016) and Zyoud et al. (2016) that Fuzzy TOPSIS was more accurate than the other used models in their reports. This paper examined the application of three MCDA techniques in local land use type planning process for a small area. Implementation of three different MCDA techniques enabled a comparative analysis of the criteria ranking, crops priority order and preferred land units. This research also adds a new dimension to the comparative analysis of MCDA techniques by considering the scale and purpose of the decision making. This is particularly important in cultivation priority planning decisions, where the scale and scope of the planning set the expectations for identifying the spatial extent of the proposed development.

The result of comparative analysis in our study showed that differences between criteria ranking in AHP and Fuzzy AHP models and crops ranking in MCDA (SAW, TOPSIS and Fuzzy TOPSIS) do not necessarily result in selecting different options (as a focal point) but rather the differences are more significant in the spatial extent of the selected options. This finding provides a new direction for selecting MCDA method for cultivation priority planning purposes. If the planning wants to identify priority areas for cultivation as a focal point, simpler MCDA methods such as SAW should be sufficient. In this situation, selecting more sophisticated techniques like Fuzzy TOPSIS, which can only be seen as a black box by users, will not necessarily generate different outcomes (Zyoud et al., 2016).

This important issue must be noticed that application of different aggregation methods in Fuzzy AHP leads to differences in outputs in terms of priority weights and finally in values of CCs for priority crops in Fuzzy TOPSIS. These differences among Fuzzy TOPSIS compared to SAW and TOPSIS are related to use of different mathematical functions, twin comparing nature of alternative (crop) from positive and negative ideal, data standardization as well as suitable weights. Moreover, if different fuzzy fundamental scales must be applied, there will be differences in computed priority weights (Lee, 2014). The selection of the

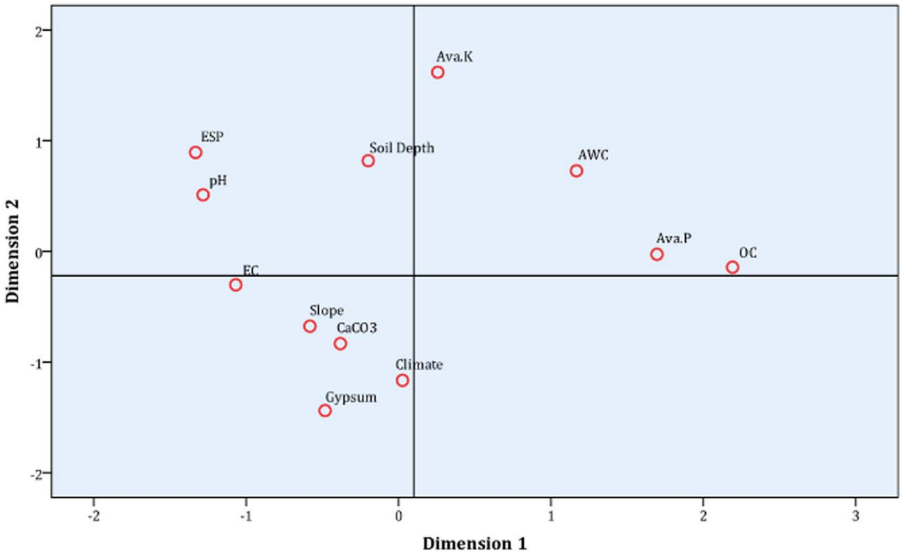

Fig. 4. Euclidean distance among criteria.

most appropriate aggregation method depends on its performance to produce rational outputs such as not too many zero weights (Zyoud et al., 2016). Other authors emphasized that fuzzy operators that lead to null weight of criteria should be avoided (Junior et al., 2014). Sometimes, the selection of the method depends on the homogeneity of the evaluations (i.e. in case the evaluations were inhomogeneous; the minimum and maximum operations will be not appropriate) (Mikhailov, 2003). In our case study, the outputs in terms of weights determination in Fuzzy AHP, crops prioritization in Fuzzy TOPSIS and CCs values of options were more satisfactory for cultivation priority planning.

4. Conclusion

Modeling of cultivation priority planning is a multiple criteria decision making method which leads land users in way that meantime adjustment of inappropriate use of land by costs declining and beneficially increasing causes that land were protected for futures exactly. Cultivation priority planning also causes that land was evaluated and their potential was determined for feasible uses. This planning could assist land users, with suitable use of land, existence problems decreased and guaranteed social, economical and environmental objectives including dandyism, employing and land sustainable. Therefore, in this article, three MCDA approaches were presented to uphold decision making in prioritizing a set of crops cultivation management strategies. These approaches were tested on a cultivation priority system for maize, rape and soybean crops in a part of Dasht-e-Moghan lands in northwest of Iran by involving policy makers and users. Their engagement was considered in two phases. First, when the decision problem structure was defined to identify the decision problem dimensions, the evaluation criteria, options and their interactions using AHP and Fuzzy AHP. Second phase is to allocate the value of the different options for cultivation priority planning via SAW, TOPSIS and Fuzzy TOPSIS. The introduced integrated methodology is based on two steps: criteria weighting and crops prioritization. The potential of this methodology is declared by its ability to ponder prioritization cases preferences and concerns. The SAW, TOPSIS and Fuzzy TOPSIS used AHP and Fuzzy AHP results in terms of weights of evaluation criteria as inputs. The methodology used the linguistic variables in the evaluation process and then converted them into fuzzy numbers for Fuzzy TOPSIS. This activity ensured the evaluation process to be more realistic as the evaluation process has fuzziness in its nature, and is not a precise one. A computational tool has been developed to allow multiple calculations, for statistical analysis with the aim to explore the sensitivity of outputs towards the changes in inputs especially weight changes. This helped to derive the robustness of the options ranking results. For the case study, it was possible to account for all concerns of the participating decision makers. The MCDA allowed to successfully introducing the basics of integrated cultivation priority planning management. Additionally, it was possible to expand the dimensions of the decision problem beyond the economic domain to cover environmental, land sustainability, potentially health and safety issues. The boundary conditions were decisive in determining the priorities of decision makers in context of selecting the most appropriate options.

The outputs of the statistical analyses showed, to a large extent, stability in the ranking of most and least preferred options. This can be

Table 3
Principal component analysis of soil and land variables (criteria) in study area.

Principal component	Eigen value	Component variance	Cumulative variance
PC1	2.79	23.24	23.24
PC2	1.64	13.66	36.90
PC3	1.59	13.23	50.14
PC4	1.36	11.35	61.49
PC5	1.12	9.35	70.85

Coefficient's maximum values of criteria for PC1 to PC5

AWC	ESP	EC	Gypsum	pH	Depth	$CaCO_3$	Slope	Climate	Ava. P	OC	Ava. K
0.831	0.807	0.797	0.674	0.654	0.645	0.537	0.525	0.460	0.418	0.402	0.358

Table 4
Criteria weights used in cultivation priority planning methods (SAW and TOPSIS).

Crop	Depth	$CaCO_3$	Gypsum	EC	ESP	pH	Slope	Climate	CR
Maize	0.227	0.039	0.082	0.127	0.161	0.098	0.248	0.018	0.017
Rape	0.195	0.041	0.168	0.074	0.08	0.131	0.289	0.022	0.005
Soybean	0.198	0.031	0.239	0.049	0.046	0.138	0.285	0.014	0.016

EC Electrical Conductivity, *ESP* Exchangeable Sodium Percentage, *pH* Hydrogen Potential, *CR* Consistency Ratio.

Table 5
Criteria TFNs weights used in Fuzzy TOPSIS method.

Criteria	Maize	Rape	Soybean
Depth	(0.175, 0.228, 0.296)	(0.130, 0.183, 0.250)	(0.138, 0.187, 0.252)
$CaCO_3$	(0.027, 0.040, 0.064)	(0.031, 0.043, 0.062)	(0.026, 0.036, 0.051)
Gypsum	(0.049, 0.073, 0.110)	(0.126, 0.173, 0.241)	(0.172, 0.231, 0.304)
EC	(0.085, 0.120, 0.169)	(0.060, 0.080, 0.112)	(0.045, 0.059, 0.081)
ESP	(0.116, 0.165, 0.229)	(0.069, 0.093, 0.128)	(0.037, 0.050, 0.071)
pH	(0.073, 0.100, 0.138)	(0.090, 0.133, 0.193)	(0.095, 0.141, 0.213)
Slope	(0.191, 0.253, 0.327)	(0.202, 0.273, 0.361)	(0.210, 0.276, 0.357)
Climate	(0.016, 0.022, 0.031)	(0.017, 0.022, 0.030)	(0.015, 0.019, 0.028)
CR	0.016	0.005	0.009

related to the strong preference of the preferred options and strong aversion of less preferred ones. The mean comparison calculations of scores confirmed the outputs of statistical analyses in terms of the most robust aggregation method. Cultivation priority pattern was maize-rape-soybean by three MCDA methods for all of the land units in study area. Statistical analyses identified that Fuzzy TOPSIS results were more accurate than the others. In comparison with other MCDA techniques that have been conducted in the field of land suitability management, this methodology showed simplicity and practicality. It was easy to be understood by decision makers in terms of implementing the required evaluations towards criteria and rating of options. We assume that the introduced MCDA approach is useful for land utilities in terms of realizing a better understanding and assessment of components of cultivation priority planning management strategies. It encourages group decision making approaches in principle and in practice with the aim to achieve consensus and concrete actions towards critical issues in land use management realm. Therefore, the introduced methodology can be upgraded to develop a sorting model for calculating crops prioritization performance indicators.

Table 6
Landscape and soil requirements for maize, oilseed rape and soybean irrigated (sprinkler irrigation) cultivation.

Rating scale	100	95	85	60	40	25	0	References
Topography(T)								
Slope (%)	Cs	0–2	2–5	5–8	8–16	16–25	> 25	IIASA and FAO, 2012
Physical soil characteristics (S)								
Texture/structure	Cs	CL, SiCL, SCL, C < 60s	L, Si, SiL, SC, SiC, C > 60s,	SL, C > 60v	LS, Cm, SiCm	fS, LcS	cS	IIASA and FAO, 2012
Coarse fragment (vol%)	Cs	0–3	3–15	15–35	35–55		> 55	IIASA and FAO, 2012
Soil depth(cm)	Cs	> 100	100–75	75–50	50–20		< 20	IIASA and FAO, 2012
$CaCO_3$ (%)	Maize	1.2–6	6–15	15–22	22–30	30–35	> 35	IIASA and FAO, 2012
	Soybean		0–1.2					
	Rape	1.2–6	6–12	12–20	20–25	25–30	> 30	
			0–1.2					
Gypsum (%)	Maize	0–2	2–4	4–10	10–15	15–20	> 20	IIASA and FAO, 2012
	Rape	0–1	1–2	2–3	3–5	5–7	> 7	
	Soybean	0–0.1	0.1–0.2	0.2–1	1–2	2–3	> 3	
AWC(cm/1.2 m Soil depth)	Cs	> 15	15–13	13–11	11–7.5	< 7.5		FAO, 1979, 2006
Soil fertility characteristics(F)								
$pH_{(H2O)}$	Maize	6.6–6.2	6.2–5.8	5.8–5.5	5.5–5.2	< 5.2		IIASA and FAO, 2012; FAO, 2012
		6.6–7	7–7.8	7.8–8.2	8.2–8.5	> 8.5		
	Rape	6.25–6	6–5.6	5.6–5.2	5.2–4.8	< 4.8		
		6.25–6.5	6.5–7	7–8	8–8.2	> 8.2		
	Soybean	6.5–6	6–5.5	5.5–5.4	5.4–5.2	< 5.2		
		6.5–7	7–7.5	7.5–7.8	7.8–8.2	> 8.2		
Organic carbon (%)	Cs	> 0.8	0.8–0.4	< 0.4				Sys et al., 1993
Available phosphorus ($mg\ kg^{-1}$)	Maize	> 16	16–14	14–10	10–6.5	< 6.5		Gheibi et al., 2014
	Rape	> 20	20–18	18–13	13–8.5	< 8.5		Noorgholipour et al., 2014
	Soybean	> 15	15–13	13–9	9–6	< 6		Warncke et al., 2004
Available potassium ($mg\ kg^{-1}$)	Maize	> 250	250–220	220–155	155–100	< 100		Gheibi et al., 2014
	Rape	> 220	220–195	195–135	135–90	< 90		Noorgholipour et al., 2014
	Soybean	> 180	180–160	160–110	110–75	< 75		Warncke et al., 2004
ACEC($cmol^{(+)}$/kg clay)	Cs	> 24	24–16	< 16(−)	< 16(+)			IIASA and FAO, 2012
Salinity and alkalinity(N)								
EC (dSm^{-1})	Maize	0–1	1–3	3–5	5–7	7–10	> 10	IIASA and FAO, 2012
	Rape	0–1	1–2	2–4	4–6	6–10	> 10	
	Soybean	0–2	2–5.5	5.5–8	8–10	> 10		
ESP (%)	Maize	0–3	3–6	6–12	12–18	18–24	> 24	IIASA and FAO, 2012
	Rape	0–4	4–8	8–16	16–24	> 24		
	Soybean	0–4	4–8	8–16	16–24	> 24		

Cs crops including maize, rape and soybean, *m* massive, *s* blocky structure, *v* vertisol structure, C < 60 clay, C > 60 very fine clay.

Table 7
Scores calculated for crops cultivation priority determination in land units using different methods.

Land Unit	SAW			TOPSIS			Fuzzy TOPSIS		
	Soybean	Rape	Maize	Soybean	Rape	Maize	Soybean	Rape	Maize
1	0.309	0.340	0.351	0.215	0.369	0.416	0.198	0.367	0.435
2	0.309	0.340	0.351	0.215	0.369	0.416	0.198	0.367	0.435
3	0.309	0.340	0.351	0.215	0.369	0.416	0.198	0.367	0.435
4	0.307	0.340	0.353	0.187	0.393	0.420	0.147	0.367	0.486
5	0.307	0.340	0.353	0.187	0.393	0.420	0.147	0.367	0.486
6	0.288	0.330	0.382	0.131	0.303	0.566	0.077	0.299	0.624
7	0.290	0.336	0.374	0.133	0.336	0.531	0.090	0.340	0.570
8	0.290	0.329	0.381	0.132	0.308	0.560	0.088	0.291	0.621
9	0.303	0.341	0.356	0.206	0.364	0.430	0.159	0.374	0.467
10	0.315	0.338	0.347	0.301	0.341	0.358	0.235	0.360	0.405
11	0.306	0.341	0.353	0.242	0.357	0.401	0.179	0.376	0.445
12	0.291	0.335	0.374	0.136	0.331	0.533	0.080	0.332	0.588
13	0.296	0.334	0.370	0.144	0.333	0.523	0.095	0.326	0.579
14	0.291	0.335	0.374	0.136	0.331	0.533	0.080	0.332	0.588
15	0.297	0.344	0.359	0.160	0.383	0.457	0.109	0.395	0.496
16	0.296	0.343	0.361	0.155	0.378	0.467	0.095	0.390	0.515
17	0.292	0.322	0.386	0.142	0.241	0.617	0.084	0.248	0.668
18	0.294	0.340	0.366	0.149	0.349	0.502	0.081	0.367	0.552
19	0.297	0.345	0.358	0.170	0.388	0.442	0.120	0.398	0.482
20	0.310	0.340	0.350	0.245	0.361	0.394	0.209	0.368	0.423
21	0.297	0.345	0.358	0.170	0.388	0.442	0.120	0.398	0.482
22	0.297	0.345	0.358	0.170	0.388	0.442	0.120	0.398	0.482
23	0.299	0.342	0.359	0.171	0.378	0.451	0.130	0.385	0.485
24	0.297	0.322	0.381	0.152	0.258	0.590	0.124	0.249	0.627
25	0.297	0.322	0.381	0.152	0.258	0.590	0.124	0.249	0.627
26	0.299	0.334	0.367	0.180	0.328	0.492	0.149	0.332	0.519
27	0.303	0.341	0.356	0.222	0.363	0.415	0.166	0.374	0.460
28	0.299	0.334	0.367	0.180	0.328	0.492	0.149	0.332	0.519
29	0.292	0.339	0.369	0.143	0.342	0.515	0.080	0.362	0.558
30	0.297	0.338	0.365	0.152	0.341	0.507	0.108	0.354	0.538
31	0.302	0.339	0.359	0.166	0.364	0.470	0.135	0.366	0.499
32	0.307	0.343	0.350	0.243	0.371	0.386	0.179	0.390	0.431
33	0.294	0.336	0.370	0.142	0.341	0.517	0.087	0.338	0.575
34	0.296	0.337	0.367	0.149	0.344	0.507	0.089	0.348	0.563
35	0.296	0.336	0.368	0.147	0.346	0.507	0.115	0.336	0.549
36	0.296	0.334	0.370	0.144	0.340	0.516	0.105	0.324	0.571
37	0.296	0.334	0.370	0.144	0.340	0.516	0.105	0.324	0.571
38	0.313	0.339	0.348	0.255	0.352	0.393	0.231	0.361	0.408
39	0.308	0.339	0.353	0.228	0.361	0.411	0.191	0.366	0.443
40	0.300	0.342	0.358	0.181	0.374	0.445	0.147	0.379	0.474
41	0.300	0.335	0.365	0.170	0.339	0.491	0.139	0.338	0.523
42	0.304	0.338	0.358	0.194	0.351	0.455	0.162	0.358	0.480
43	0.297	0.341	0.362	0.157	0.364	0.479	0.097	0.377	0.526
44	0.300	0.345	0.355	0.175	0.397	0.428	0.124	0.404	0.472
45	0.298	0.346	0.356	0.162	0.395	0.443	0.106	0.411	0.483
46	0.292	0.339	0.369	0.138	0.356	0.506	0.081	0.361	0.558
47	0.296	0.340	0.364	0.153	0.361	0.486	0.112	0.368	0.520
48	0.310	0.338	0.352	0.234	0.358	0.408	0.210	0.359	0.431
49	0.296	0.343	0.361	0.165	0.380	0.455	0.116	0.389	0.495
50	0.302	0.334	0.364	0.179	0.326	0.495	0.145	0.333	0.522
51	0.296	0.343	0.361	0.170	0.379	0.451	0.120	0.387	0.493
52	0.294	0.338	0.368	0.146	0.343	0.511	0.099	0.358	0.543
53	0.298	0.339	0.363	0.156	0.351	0.493	0.102	0.363	0.535
54	0.301	0.337	0.362	0.171	0.344	0.485	0.136	0.351	0.513
55	0.293	0.332	0.375	0.148	0.320	0.532	0.113	0.320	0.567
56	0.295	0.331	0.374	0.153	0.316	0.531	0.120	0.312	0.568
57	0.294	0.331	0.375	0.153	0.319	0.528	0.122	0.313	0.565
58	0.295	0.345	0.360	0.161	0.382	0.457	0.109	0.398	0.493
59	0.299	0.342	0.359	0.170	0.379	0.451	0.122	0.382	0.496
60	0.307	0.339	0.354	0.235	0.356	0.409	0.178	0.364	0.458
61	0.303	0.344	0.353	0.195	0.390	0.415	0.151	0.397	0.452
62	0.292	0.338	0.370	0.140	0.350	0.510	0.083	0.356	0.561
63	0.292	0.338	0.370	0.140	0.350	0.510	0.083	0.356	0.561
64	0.299	0.337	0.364	0.185	0.335	0.480	0.152	0.347	0.501
65	0.311	0.338	0.351	0.229	0.360	0.411	0.210	0.359	0.431
66	0.306	0.338	0.356	0.204	0.346	0.450	0.183	0.354	0.463

Table 8
Multivariate variance analysis results among prioritization methods.

Test	Value	F	Hypothesis df	Error df	*P* value
Pillai's trace	0.851	72.226	4	390	< 0.0001
Wilks' lambda	0.149	154.335	4	388	< 0.0001
Hotelling's trace	5.713	275.676	4	386	< 0.0001
Roy's largest root	5.713	557.061	2	195	< 0.0001

Table 9
Levene's test of equality of error variances.

	F	df1	df2	P value
Maize	53.641	2	195	< 0.0001
Rape	27.242	2	195	< 0.0001
Soybean	44.464	2	195	< 0.0001

Table 10
Mean comparison of scores derived from models for crops.

	Maize	Rape	Soybean
Fuzzy TOPSIS	0.514[a]	0.355[a]	0.132[c]
TOPSIS	0.474[b]	0.351[b]	0.175[b]
SAW	0.363[c]	0.338[c]	0.299[a]

Different letters show significant difference at $\alpha = 0.05$, significant difference level between FTOPSIS and TOPSIS is $\alpha = 0.4$ for Rape.

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Authors' contributions

Javad Seyedmohammadi performed the experiments and statistical analysis as well as wrote the paper. Prof. A.A. Jafarzadeh and Prof. F. Sarmadian supervised the work. Dr. F. Shahbazi and Dr. M.A. Ghorbani advised the research project. The supervisors and advisors of this research support administrative, technical and material needs.

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